Autonomous Drone for Dynamic Smoke Plume Tracking

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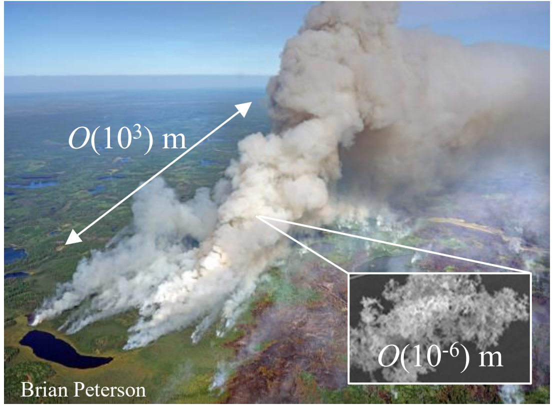
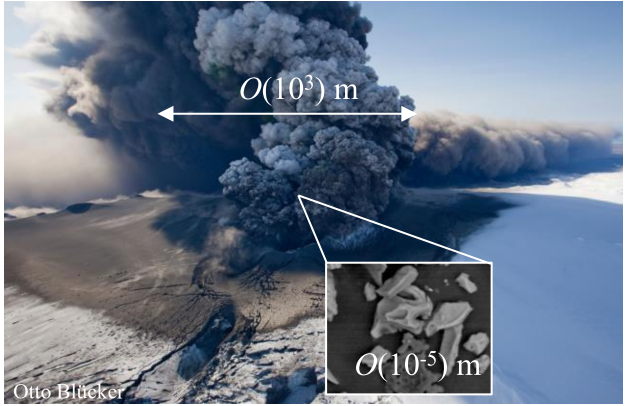
Introduction

Importance of Understanding Atmospheric Particle Transport

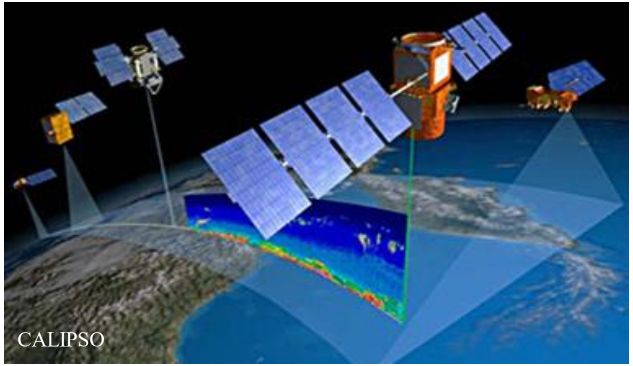

The Atlantic

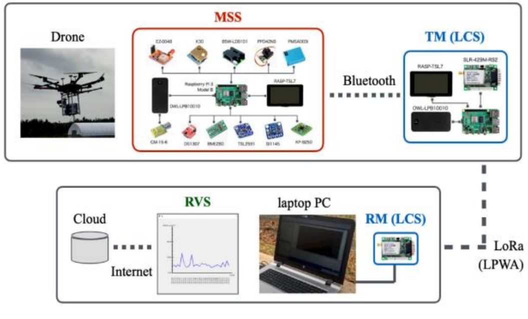

Brian Peterson


Otto Blücker

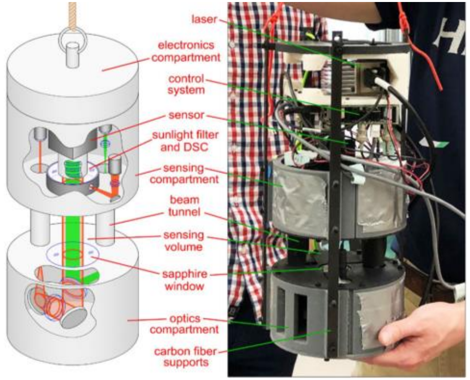
- **Significance of atmospheric particle transport: Implications for environmental monitoring, climate modeling, and impact on human health** (Kumar 2011; Kok 2012; Evangeliou 2020)
  - Smoke plume from forest fire (Jaffe 2020), volcanic ash (Butwin 2015) and movement of sand, dust or snow (Dentoni 2022; Mott 2010)
- **Particle transport in the atmosphere covers a broad range of scales**
  - From individual particles at micrometer scale to transport events spanning kilometers (Sokolik 2019)
  - Morphology and composition critically affect settling and dispersion (Lahde 2013)
- **Significant gap remains in field data measurement capabilities**
  - **Challenge: Develop a tool to measure both large-scale motion + individual particle details**

Existing Characterization Tools



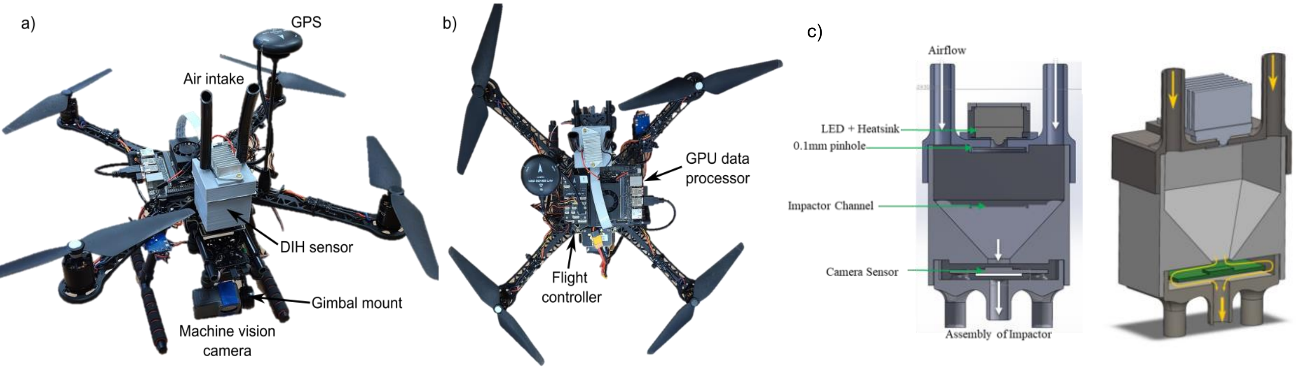


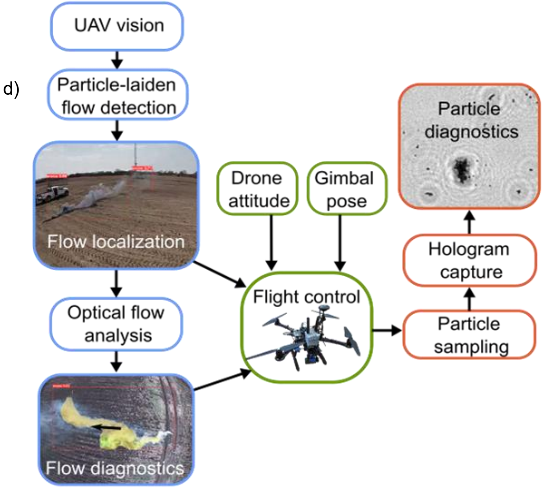
Madokoro 2021



- **Existing approaches to monitor atmospheric particle transport:**
  - **Indirect measurements:** Using satellites with LiDAR (CALIPSO by NASA; Wandinger 2005; Sokolik 2019)
  - **In-situ measurements:** Drone-based using PM sensors (Madokoro 2021), optical particle counters (Hagan 2020), or aerodynamic particle analyzers (Johnson 2018)
  - **DIH sensor-based measurements:** DIH under aircraft wing to characterize clouds (Beals 2015; HOLODEC), tethered DIH on drone to characterize pollen (Kemppinen 2020)
  - **Limitations:**
    - Satellites cover large scale motion, across continents, but **lack individual particle details**
    - Existing in-situ measurement systems rely on manual operation, **limiting their ability to autonomously adapt to dynamic and rapidly changing atmospheric flow conditions**

Bristow 2023: Autonomous Aerosol Diagnostics with UAV

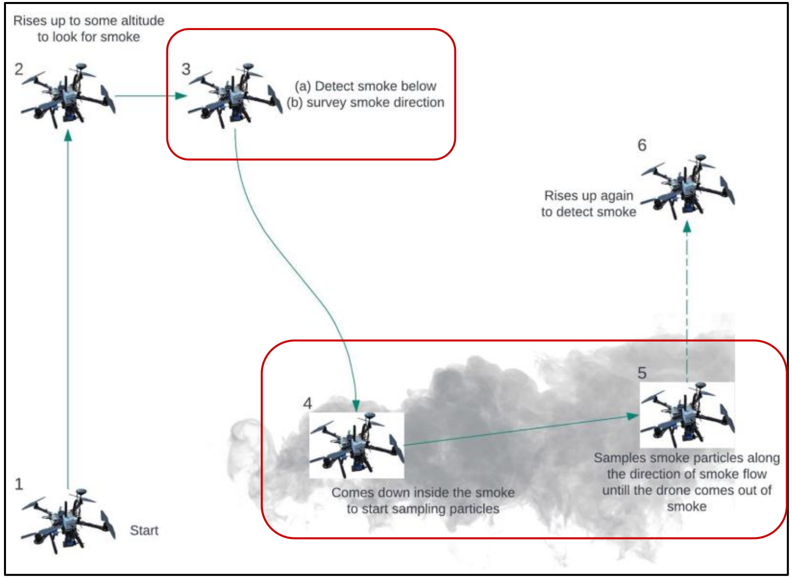




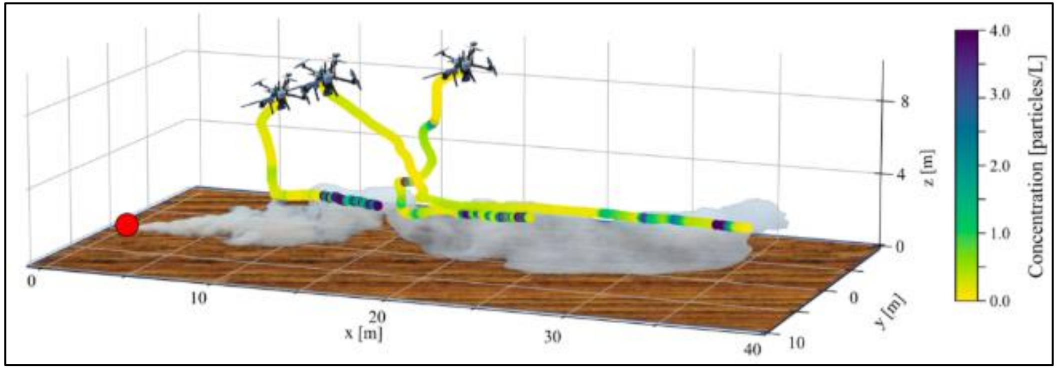
(a, b) Drone hardware, (c) DIH particle sensor and (d) overview of smoke sampling algorithm

- **Aerosol Diagnostics with UAV-based Holographic Imaging and Computer Vision:**
  - Quadrotor-based platform: Advantages in **flexibility and mobility**
  - Equipped with DIH: Provides **real-time high resolution holographic particle images**
  - Autonomy: **Deep learning and computer vision-based algorithm** to autonomously detect and follow particle-laden flows
  - Mobile measurements: **Effectively sample** particle-laden flows, such as smoke

Bristow 2023: Autonomous Aerosol Diagnostics with UAV



Overview of the Bristow's smoke sampling algorithm

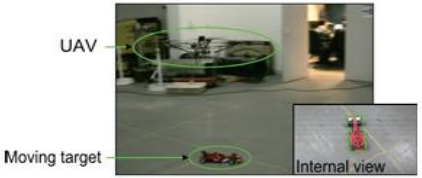


Particle diagnostics showing spatial particle concentration map along the UAV path, moving along heading estimated by optical flow

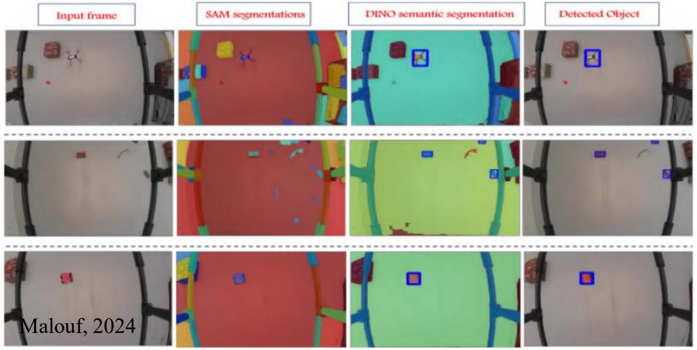
- **Limitation of Bristow 2023:**
  - **Lack of direction adaptation in realistic smoke:** Absence of feedback within smoke; in case of smoke changing direction, the system fails to detect and maneuver back in, resulting in inaccuracies
- **Objective:** Develop an autonomous drone that detects, follows, and **remains within a dynamically evolving smoke plume** under highly unsteady wind conditions

Related Works

Object Detection and Tracking in Drones

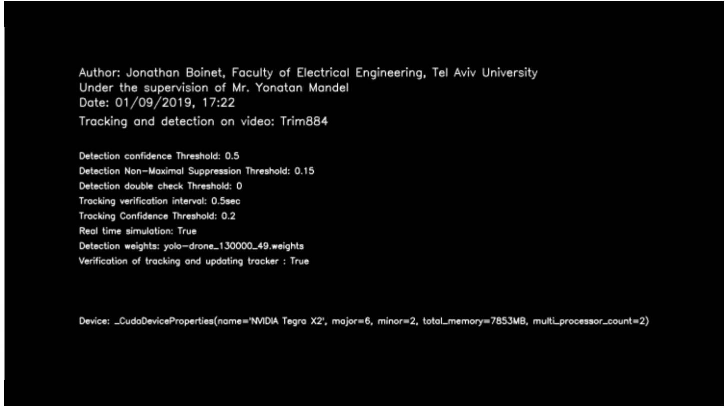


Drone tracking dynamic targets



Malouf, 2024

Detection of target (e.g., drones and RC cars) from drone

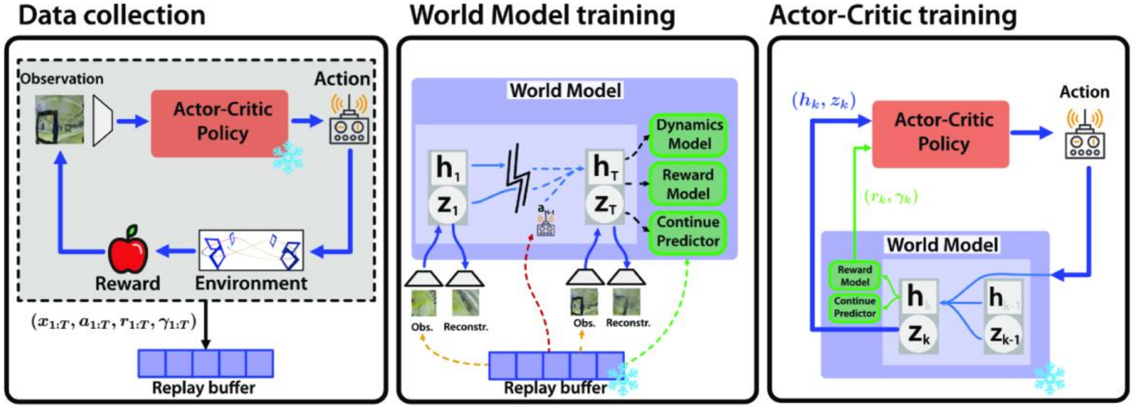


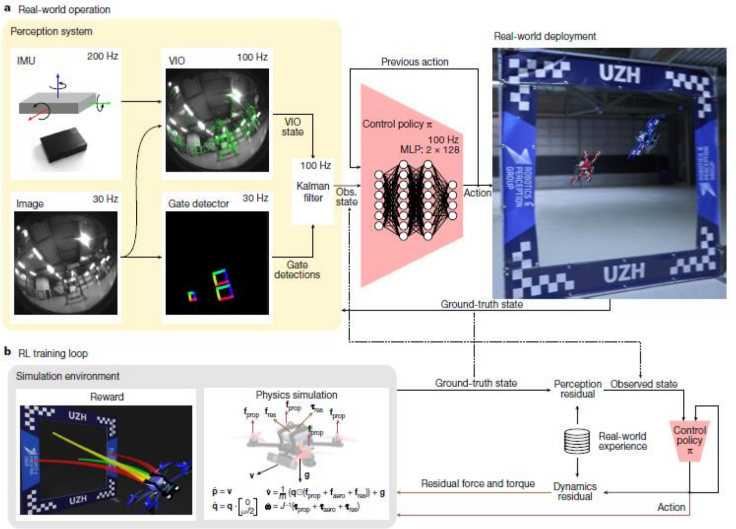
```
Author: Jonathan Boinet, Faculty of Electrical Engineering, Tel Aviv University
Under the supervision of Mr. Yonatan Mandel
Date: 01/09/2019, 17:22
Tracking and detection on video: Trim884

Detection confidence Threshold: 0.5
Detection Non-Maximal Suppression Threshold: 0.15
Detection double check Threshold: 0
Tracking verification interval: 0.5sec
Tracking Confidence Threshold: 0.2
Real time simulation: True
Detection weights: yolo-drone_130000_49.weights
Verification of tracking and updating tracker : True


Device: _CudaDeviceProperties(name='NVIDIA Tegra X2', major=6, minor=2, total_memory=7853MB, multi_processor_count=2)
```

Drone tracking target drone using YOLO on a Jetson TX2

- **Real-time vision-based target object detection and following**:
  - **Target object detection:** Using traditional image processing (Teuliere 2011; Malouf 2024) or deep learning approaches (Kanellakis 2017; Ramachandran 2021; Zaidi 2022)
  - **Target tracking:** Using PID controllers (Malouf 2024) often coupled with Kalman filtering (Barisic 2019)
  - **Limitations in context of our objective:**
    - Atmospheric particle transport, such as smoke, is highly dynamic fluids, differing significantly from regular non-deformable solid objects (Teuliere 2011; Malouf 2024; Cesetti 2009)
    - Optimized for performing in controlled environments

Deep Reinforcement Learning for Drone Control





World-model-based RL training pipeline (left) and the Swift, a DRL framework for autonomous drone racing and agile navigation (right)

➢ Deep Reinforcement Learning (DRL) for Vision-Based Navigation in Drones:

- Enhanced **adaptability and robustness** in dynamic and unpredictable environments (Aburaya 2024)
- Vision and depth-based localization methods **enable object avoidance, tracking, and agile navigation** like drone racing (Kaufmann 2023; Ma 2023; Zhou 2019)
- **Limitations in context of our objective:**
  - No prior research focused specifically on using these methods to track and follow atmospheric flows, such as smoke plumes

Related Works

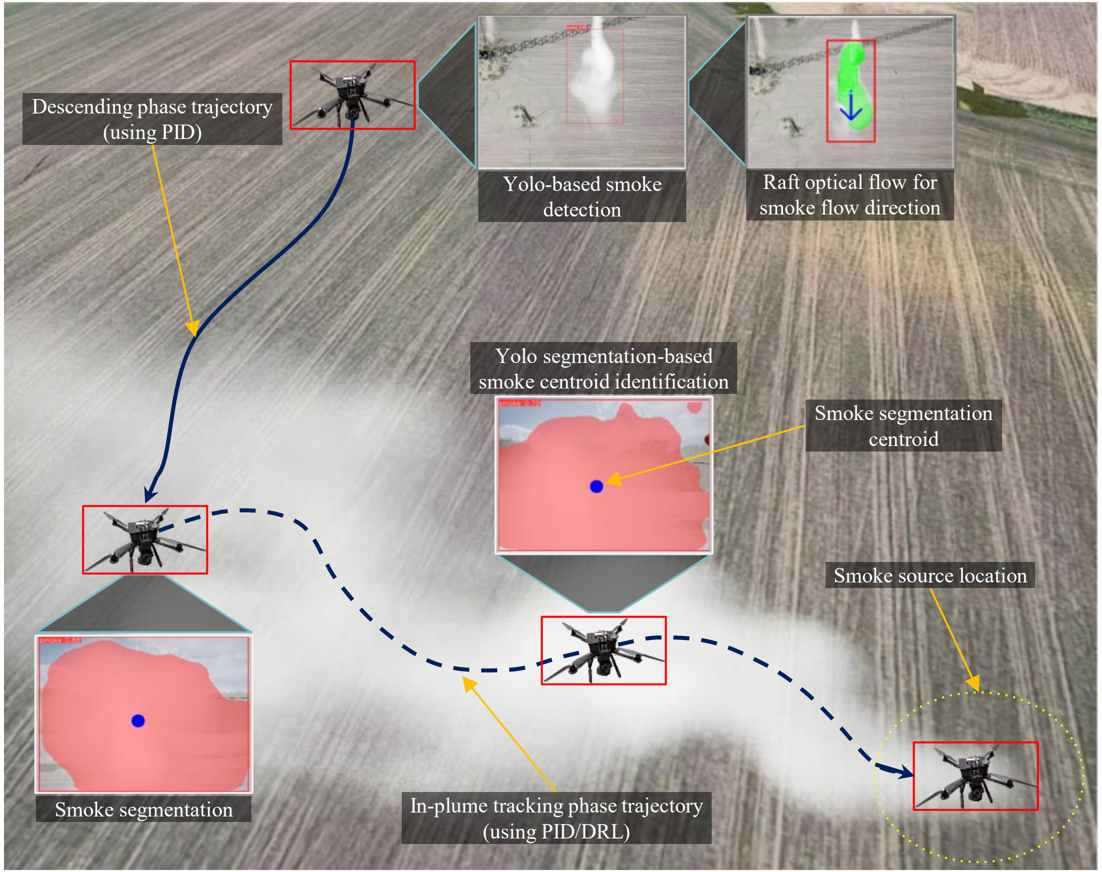
- **Summary:**
    - **No existing research specifically focused on utilizing drones to track atmospheric particle transport such as smoke plumes**
    - Relevant studies primarily concentrated on using drones to track predictable static/dynamic objects such as vehicles, people, or other drones
    - Drones typically use vision-based PID controllers to follow/track regular dynamic targets
    - DRL-based drone controllers have been used in object avoidance and agile navigation

- **Challenges in tracking atmospheric flows:**
    - **Highly dynamic fluid target:** unlike rigid objects, smoke plumes have no fixed boundary or shape
    - **Nature of target:** Unlike solid objects, **smoke plumes are highly dynamic fluids**
    - **Constant evolution:** Requires **real-time adaptation to constantly changing shape and density**
    - **External conditions:** Factors like **wind and turbulence** affect tracking performance
    - **Resource constraints:** Efficient algorithms are needed to **track smoke plumes in real-time with limited onboard resources**

Methodology

Overview

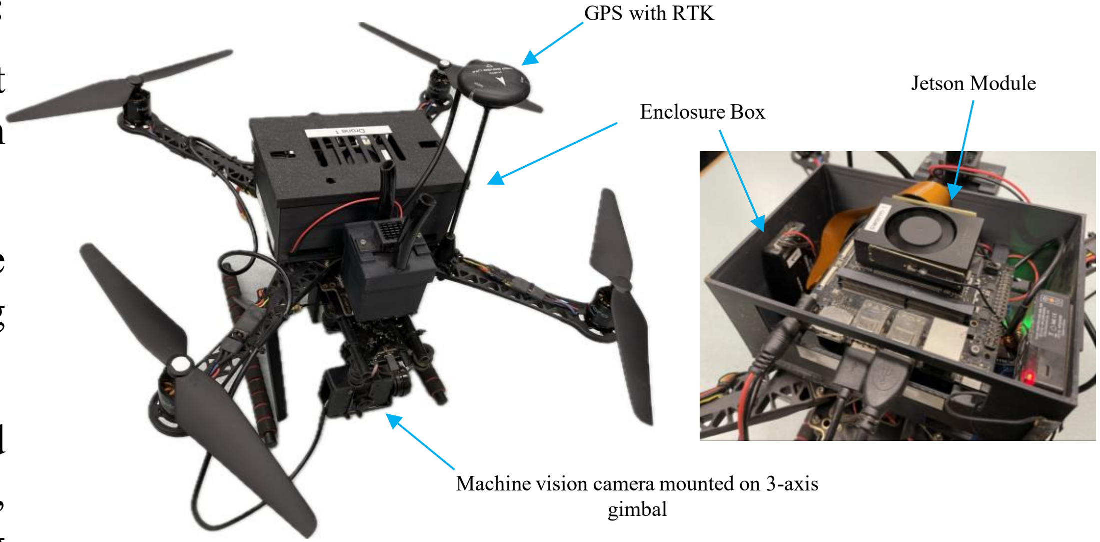
- **Descending Phase:** Positioning above smoke plume, capturing a top-down view. Once smoke is detected, descend to smoke dispersion region
- **In-Plume Smoke Tracking Phase:** Continuous segmentation of smoke and find the centroid of the densest smoke
- **PID Controller for Smoke Tracking**: Adjust drone position based on the error between the camera's center and the smoke centroid
- **DRL Controller for Smoke Tracking:** Predicts drone motion from the smoke mask, learning to track denser regions even under unsteady wind conditions



Overview of the autonomous drone-based smoke plume tracking system

Hardware

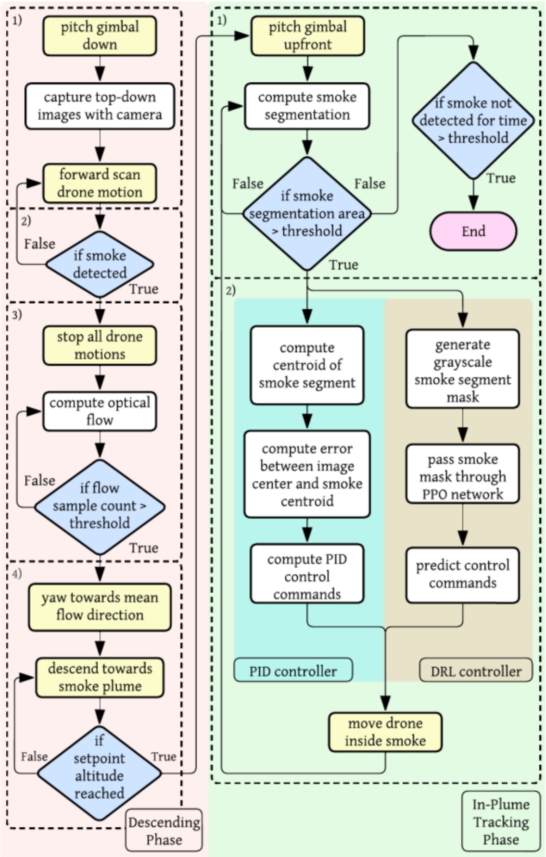
- **Upgrades on Bristow 2023 hardware:**
  - **Pixhawk 6C**: Upgraded flight controller for more stable flight in dynamic environment
  - **GPS with RTK:** Precise drone location, used for smoke tracking performance evaluation
  - **Machine vision camera:** Upgraded with **ArduCam 12MP** camera, reducing latency while maintaining high image quality



Autonomous drone-based smoke tracking system hardware

  - **Onboard GPU:** Upgraded to Nvidia **Jetson Orin Nano** (40 TOPS), reducing inference time for real-time deep learning, doubling onboard compute capacity
  - **Enclosure Box:** Custom 3D printed enclosure for onboard electronics

Autonomous Smoke Tracking Algorithm



Framework of autonomous drone operation algorithm

➢ Descending Phase:

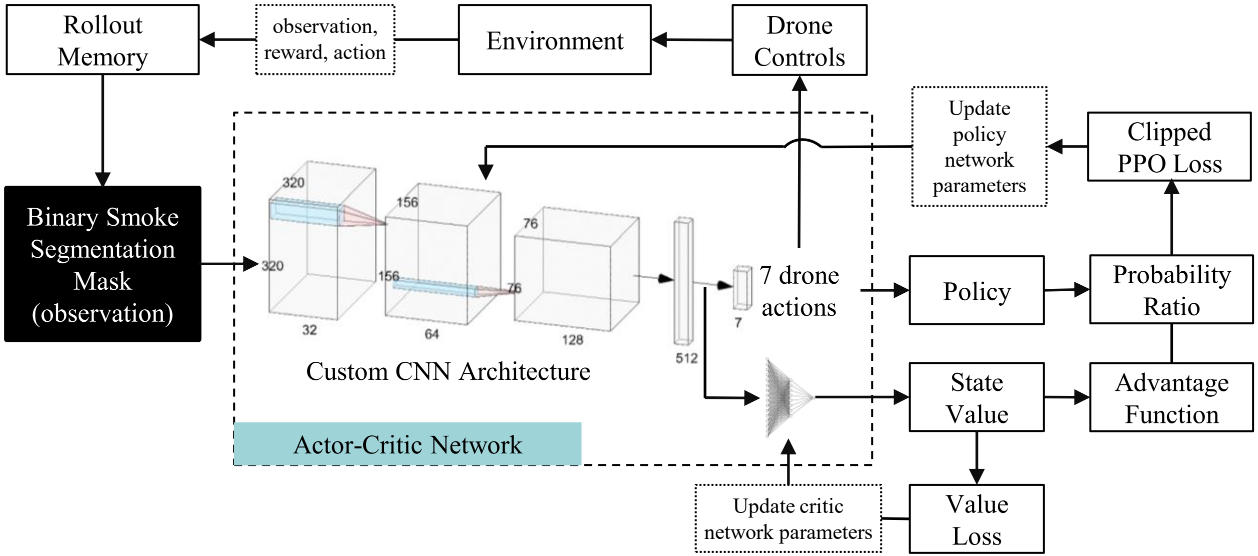
- **Hovering Above Smoke:** Drone hovers above plume; gimbal set for top-down view of smoke
- **Smoke Detection:** YOLOv8m detects smoke bounding box
- **Flow Direction:** RAFT optical flow computes smoke flow direction
- **Yaw Alignment & Descent:** Drone aligns with smoke flow; PID used to descend in the plume dispersion region

➢ In-Plume Tracking Phase:

- **Smoke Segmentation:** YOLOv8m segments densest smoke region
- **Trajectory Control:**
  - **PID:** Corrects drone's position using smoke centroid
  - **DRL:** Takes segmentation mask as input to predict drone motion towards the densest smoke
  - **Manual Controller Switch:** Current system allows operator-controlled switching between PID and DRL

DRL Drone Control: Proximal Policy Optimization (PPO)

(a) PPO Architecture (training) :



Rollout Memory

observation, reward, action

Environment

Drone Controls

Binary Smoke Segmentation Mask (observation)

Update policy network parameters

Clipped PPO Loss

7 drone actions

Custom CNN Architecture

Actor-Critic Network

Policy

Probability Ratio

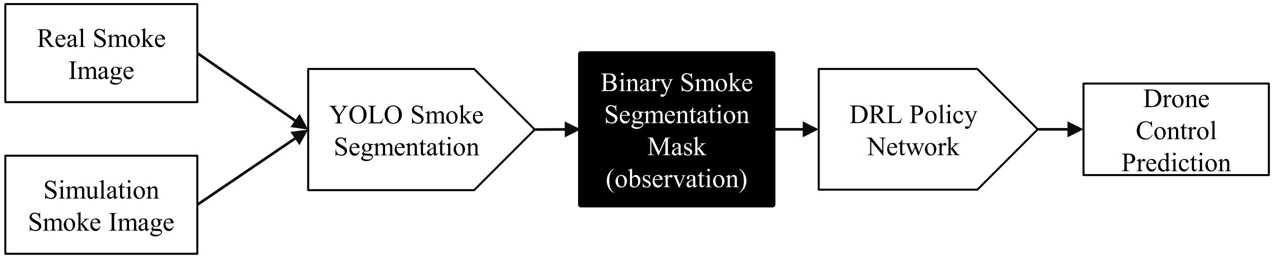
State Value

Advantage Function

Value Loss

Update critic network parameters

(b) Inference and Sim2Real Transfer :



Real Smoke Image

Simulation Smoke Image

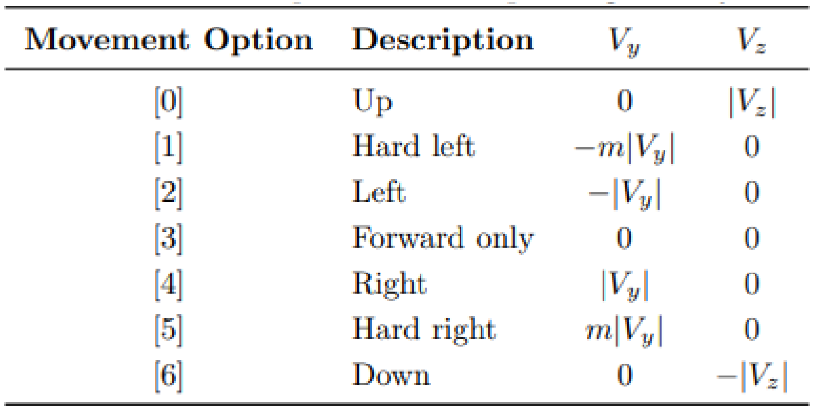
YOLO Smoke Segmentation

Binary Smoke Segmentation Mask (observation)

DRL Policy Network

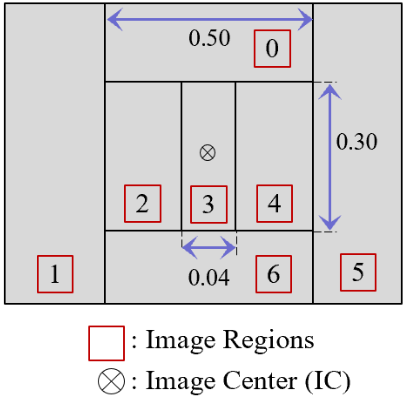
Drone Control Prediction

DRL Drone Control: Proximal Policy Optimization (PPO)



Movement Option	Description	V_y	V_z
[0]	Up	0	$\lvert V_z\rvert$
[1]	Hard left	$-m\lvert V_y\rvert$	0
[2]	Left	$-\lvert V_y\rvert$	0
[3]	Forward only	0	0
[4]	Right	$\lvert V_y\rvert$	0
[5]	Hard right	$m\lvert V_y\rvert$	0
[6]	Down	0	$-\lvert V_z\rvert$

Discrete action space and corresponding velocity commands



X_s in 0 or 6:
    if [X_s= pred]: R=+1 *else:* -1
X_s in [1-5]:
    if [pred = 0 or 6]: R= -1
    else if [X_s= pred]: R=+1
    else if [$X_s \approx$ pred]: R=+0.5 or 0 *else:* -1
    1) X_s=1: *if* [pred=2]: R=+0.5
        else if [pred=3]: R=0 *else:* -1
    2) X_s=2: *if* [pred=1 or 3]: R=+0.5 *else:* -1
    3) X_s=3: *if* [pred=2 or 4]: R=+0.5 *else:* -1
    4) X_s=4 and X_s=5: R is symmetrical as X_s=2 and X_s=1 about IC respectively

Illustration of reward function, where Xs is the segmented smoke's centroid location, pred is the DRL controller's prediction, and R is the reward.

Each frame is partitioned into 7 regions symmetrical about the image center (IC), with the dimensions indicating fractions of the total image length, and the red boxes with numbers denote the image regions

Simulation Assessment

High-Fidelity Simulation Environment

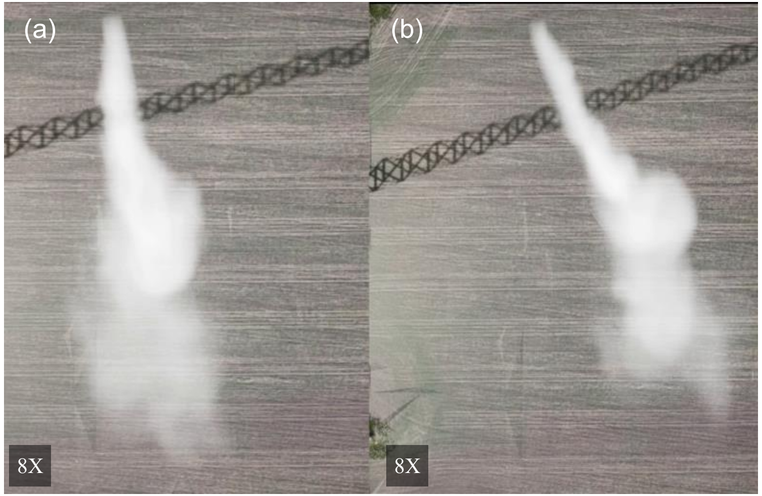

Real photo of Eolos site at UMore Park


Recreated UMore Park environment in Unreal Engine 5.1

- **Simulation Environment (deployment site, smoke-wind generation and drone simulation)**
  - Recreated the real field deployment site: **Eolos Wind Energy Research Consortium** at UMore Park in Rosemount, Minnesota
  - **High-fidelity simulation environment developed in Unreal Engine 5.1**
  - Integrated AirSim, PX4 SITL, MAVROS and WSL to simulate realistic drone autonomy
  - Enabled **rapid algorithm development**, **DRL-based PPO training and evaluation** in diverse smoke-wind conditions prior to real-world deployment

Smoke Generation in Simulation

Simulated black and white smoke



Simulated (a) steady unidirectional and (b) unsteady smoke flows

```
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
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size of segment: 0 | skip: True
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size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
size of segment: 0 | skip: True
2secs past from the last detected smoke | done: True

Resetting drone position to detect smoke from top ...

-------------------------------- Reset ------------------------------------
Coming down to setpoint altitude!
```
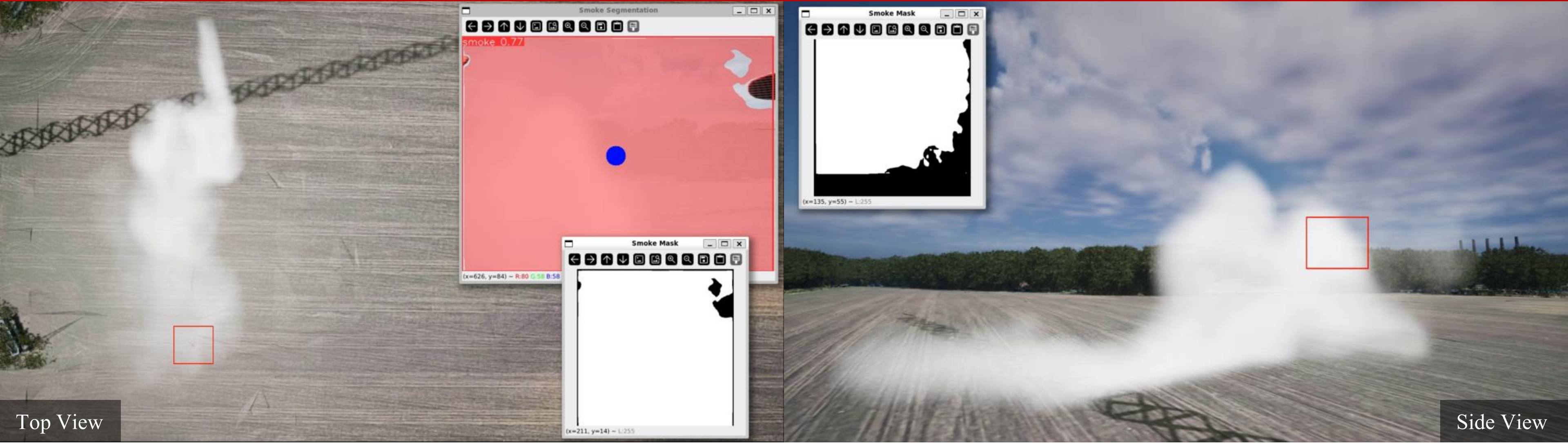

DRL training in Unreal Engine simulation

- **Simulating smoke-wind scenarios in Unreal Engine:**
  - **Smoke with controlled wind:** Simulated using Niagara plugin (Niagara Fluids and Chaos Niagara)
  - **Wind field:** Controlled via Niagara blueprints, supporting steady and time-varying wind vectors
  - **DRL was trained for 5 hours / 1 million timesteps:** Smoke-wind conditions alternated between unidirectional steady and unsteady (low and high-frequency fluctuations) flows

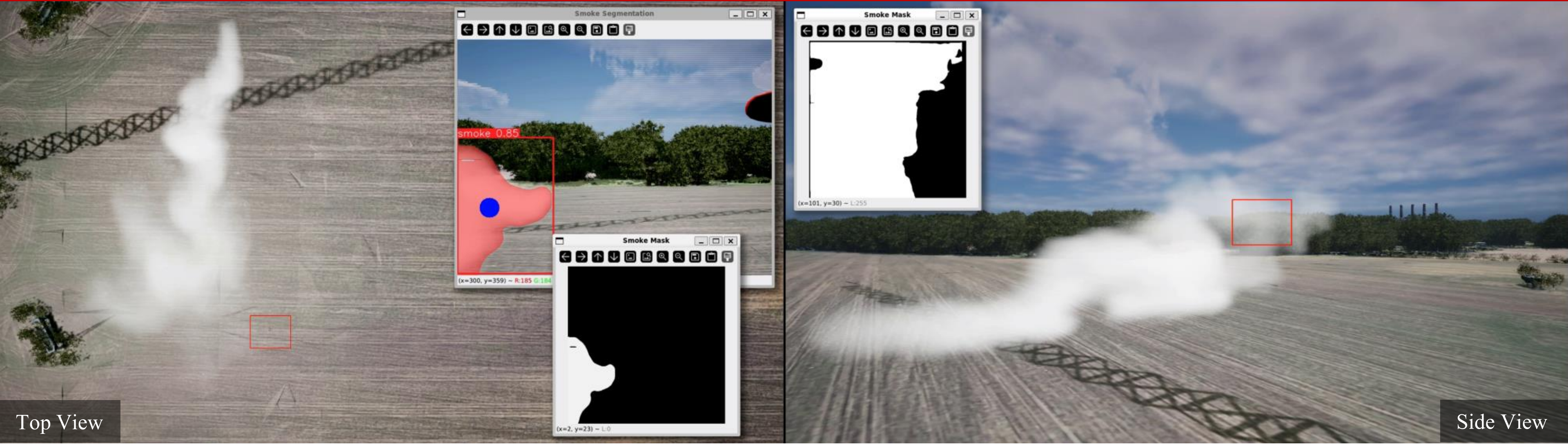
Smoke Tracking: PID Controller



Drone autonomously tracking smoke plume using PID
[red bounding box: drone location]

- **Autonomous smoke tracking using PID:**
  - Smoke segmentation using YOLOv8-seg model
  - Drone controlled using PID controller based on positional error of the segmentation centroid
  - Simulation demonstrates drone entering smoke, tracking smoke along its flow path, and ultimately reaching source of smoke

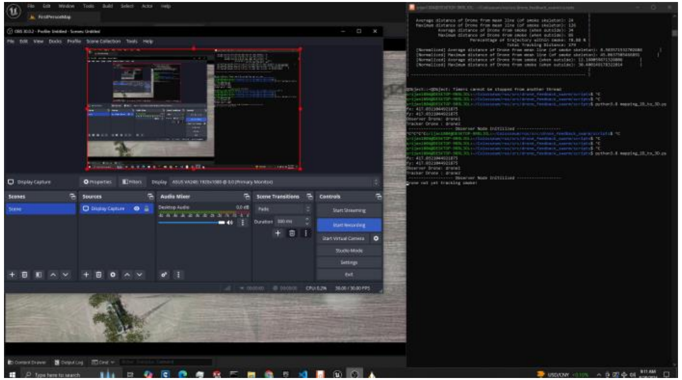
Smoke Tracking: DRL Controller

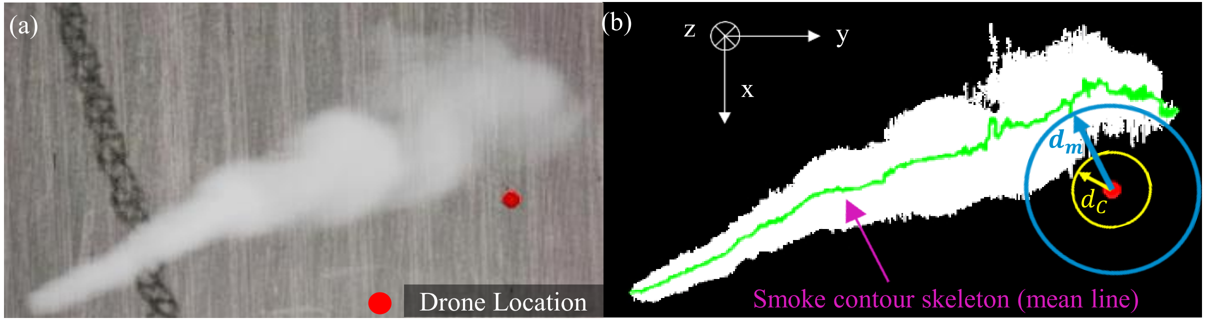


Drone autonomously tracking smoke plume using DRL
[red bounding box: drone location]

- **Autonomous smoke tracking in simulation using DRL:**
  - Smoke segmentation using YOLOv8-seg model
  - Drone controlled using PPO-based DRL controller which uses smoke-segmentation mask as input
  - **Unlike PID, the DRL policy adapts to plume deformation by learning to predict motion toward higher-density regions from segmentation masks**

Smoke Tracking Evaluation Metrics





(a) Top-view plume image and (b) smoke contour with tracking evaluation metrics

- **Smoke tracking evaluation:**
  - Tracker drone location projected in the top-down view of smoke
  - Smoke contour and mean line (skeleton) are detected in the top-down view
- **Five metrics used for performance evaluation (**L_{ref} **is the total smoke tracking length):**
  - Average distance from the mean line: $\tilde{\mu}_m = mean(d_m)/L_{ref}$
  - Maximum distance from the mean line: $\tilde{d}_{m,max} = max(d_m)/L_{ref}$
  - Average distance when outside the smoke plume: $\tilde{\mu}_c = mean(d_c)/L_{ref}$
  - Maximum distance when outside the smoke plume: $\tilde{d}_{c,max} = max(d_c)/L_{ref}$
  - Percentage of time inside the smoke plume: $\tilde{t}_R$

Simulated Smoke-Wind Conditions

- **Four smoke-wind scenarios simulated for smoke tracking evaluation:**
  - **Steady smoke flow (S)**: Constant streamwise wind with no fluctuations

$$V_{w,y} = 4.5 \text{ m/s} \qquad , V_{w,x} = 0 \text{ m/s.}$$

  - **Unsteady smoke flow with low-frequency fluctuating crosswind (UL):**

$$V_{w,y} = 4.5 \text{ m/s} \qquad V_{w,x} = 1.35 \sin(0.02\pi t) \text{ m/s}$$

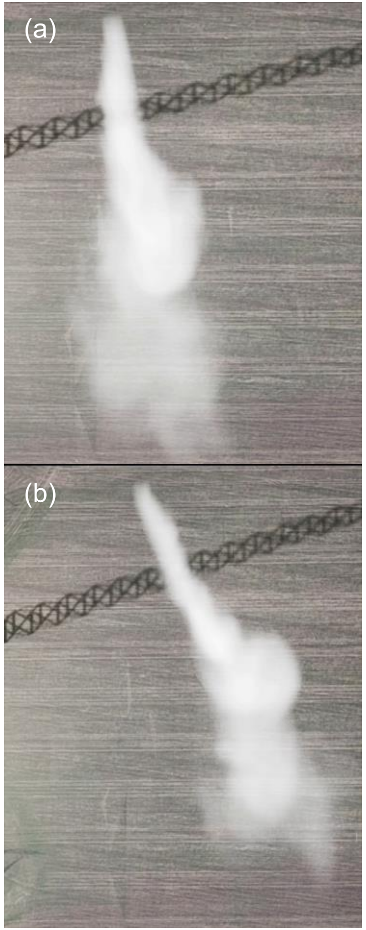
  - **Unsteady smoke flow with high-frequency fluctuating crosswind (UH):**

$$V_{w,y} = 4.5 \text{ m/s} \qquad V_{w,x} = 1.95 \sin(0.04\pi t) \text{ m/s}$$

  - **Unsteady smoke flow with 3D fluctuating crosswind (U3D):**

$$V_{w,y} = 4.5 \text{ m/s} \qquad V_{w,x} = 1.95 \sin(0.04\pi t) \text{ m/s}$$

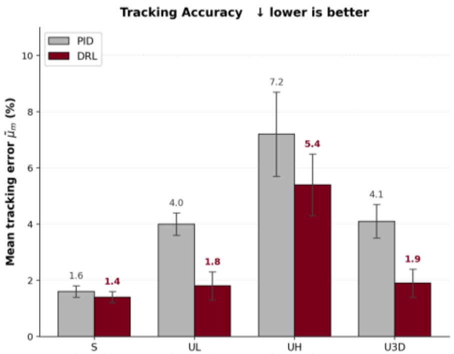
$$V_{w,z} = 0.3 \sin(0.02\pi t) \text{ m/s}$$

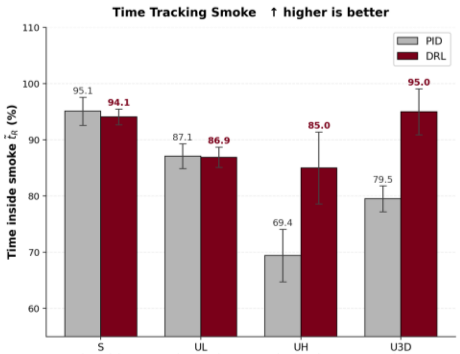


Simulated (a) steady unidirectional and (b) unsteady smoke flows

Smoke Tracking Results

		$\tilde{\mu}_m(\%)$	$\tilde{d}_{m,max}(\%)$	$\tilde{\mu}_c(\%)$	$\tilde{d}_{c,max}(\%)$	$\tilde{t}_R$ (%)
S	PID	1.6±0.2	7.5±2.1	1.4±0.6	2.9±0.7	95.1±2.5
	DRL	1.4±0.2	7.0±2.3	1.8±1.2	4.0±3.3	94.1±1.4
UL	PID	4.0±0.4	11.9±2.2	2.5±1.3	6.6±3.1	87.1±2.2
	DRL	1.8±0.5	10.1±2.3	2.5±1.1	8.4±3.3	86.9±1.8
UH	PID	7.2±1.5	28.1±10.9	5.3±3.8	18.6±7.4	69.4±4.7
	DRL	5.4±1.1	26.0±8.4	4.6±3.1	12.3±6.5	85.0±6.4
U3D	PID	4.1±0.6	15.5±6.5	4.5±2.6	12.8±5.9	79.5±2.3
	DRL	1.9±0.5	10.6±4.4	1.5±2.1	4.3±4.3	95.0±4.1


Tracking Accuracy ↓ lower is better


Time Tracking Smoke ↑ higher is better

- **Smoke tracking evaluation results:**
  - PID and DRL performance is **similar in steady unidirectional flow** (S) and **unsteady flow with low fluctuations** (UL)
  - DRL outperforms PID under challenging smoke conditions (U3D), **staying inside smoke almost 15% longer**
  - **DRL significantly reduces tracking error in unsteady environments -** e.g., in UH, max plume-edge deviation drops to 12.3% (DRL) from 18.6% (PID)
  - Under 3D fluctuation, distance from smoke mean line is 1.9% for DRL, compared to PID's 4.1%, showcasing **DRL's better adaptation to more realistic smoke fluctuations**

Field Demonstration

Field Demonstration

Drone autonomously tracking real smoke plume using PID/DRL
[red bounding box: drone location]

- **Autonomous tracking of real dynamic smoke plume (**Eolos Field Station, Rosemount, MN)**:**
  - Smoke segmentation using YOLOv8-seg model
  - Autonomous drone movements using PID and DRL-based controllers
  - Field deployment demonstrates the process of drone tracking the smoke plume, and ultimately reaching the source of the smoke

Smoke Tracking Results

	$\tilde{\mu}_m(\%)$	$\tilde{d}_{m,max}(\%)$	$\tilde{\mu}_c(\%)$	$\tilde{d}_{c,max}(\%)$	$\tilde{t}_R\ (\%)$
PID	6.4	21.0	3.6	10.0	71.2
DRL	8.1	27.8	4.1	12.2	72.7

- **Smoke tracking evaluation results in field deployment:**
  - **DRL stayed inside the plume marginally longer** (72% DRL vs 71.2% PID)
  - **PID achieved tighter smoke mean-line proximity** (6.4 PID vs 8.1 DRL)
  - **Field smoke-wind conditions could not be repeated identically across PID and DRL trials, so a direct quantitative comparison is limited**
  - Both controllers successfully tracked the dynamically shifting plume to its source - the system works end-to-end in real conditions

Conclusion and Future Work

- **Conclusion:** Developed the autonomous drone system for tracking dynamically evolving smoke plumes under unsteady wind, with DRL outperforming PID and both controllers validated in field deployments
- **Current limitation:** Both perception and control validated under restricted conditions: white smoke and moderate winds; harsher environments and varied smoke types remain untested
- **Future work:** Master–worker drone swarm: a master drone outside the plume captures the global view, guiding in-plume worker drones for more accurate tracking

- **This work has been published in ICRA 2025:** S. K. Pal, S. Sharma, N. Krishnakumar and J. Hong, "Autonomous Drone for Dynamic Smoke Plume Tracking," *2025 IEEE International Conference on Robotics and Automation (ICRA)*, Atlanta, GA, USA, 2025, pp. 303-309.

Project Website

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Questions